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# Parameter Estimation of Electric Power Transformers Using Coyote Optimization Algorithm With Experimental Verification

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**ABSTRACT** In this work, the Coyote Optimization Algorithm (COA) is implemented for estimating the parameters of single and three-phase power transformers. The estimation process is employed on the basis of the manufacturer's operation reports. The COA is assessed with the aid of the deviation between the actual and the estimated parameters as the main objective function. Further, the COA is compared with well-known optimization algorithms i.e. particle swarm and Jaya optimization algorithms. Moreover, experimental verifications are carried out on 4 kVA, 380/380 V, three-phase transformer and 1 kVA, 230/230 V, single-phase transformer. The obtained results prove the effectiveness and capability of the proposed COA. According to the obtained results, COA has the ability and stability to identify the accurate optimal parameters in case of both single phase and three phase transformers; thus accurate performance of the transformers is achieved. The estimated parameters using COA lead to the highest closeness to the experimental measured parameters that realizes the best agreements between the estimated parameters and the actual parameters compared with other optimization algorithms.

**INDEX TERMS** Coyote, PSO, Jaya, single-phase transformer, transformer equivalent circuit.

## I. INTRODUCTION

The transformer is a vital element in electrical power systems. The failure of transformer or the wrong operation affects the overall power system reliability and performance. The transformer has its own model. The parameters of the transformer model depict its performance over different conditions [1]. The accurate estimation of the transformer equivalent circuit parameters helps in efficient monitoring process of power transformers. The importance of accurate estimation process is resulted from the need to enhance the performance characteristics of transformers in both steady-state and transient cases [2], [3]. The existence of harmonics, saturation, and transient conditions in transformer affects the parameter estimation process. Thus, real time measurements were used by applying frequency response [4] or time domain analysis to obtain an accurate estimation of the transformer parameters [5]–[8]. The saturation of transformer core was considered in parameter estimation by using inrush current measurements [9]. The real time measurement process includes load terminal data, phase measurement unit (PMU), inrush current test, open circuit and short- circuit tests. This process, in most cases, requires disconnecting the transformer from operation, which is considered an impractical solution.

Optimization techniques have become the most popular strategies for solving different electrical problems such as the parameter estimation of electrical elements such as electric machines, transformers, power lines, fuel cells and photovoltaic modules, batteries, management of electrical distribution system with soft open point, optimal power flow problem [10]–[15]...etc. In the estimation problems, the optimization methods compare the actual and estimated data to minimize the deviation between them [16]–[18]. Many of optimization methods use the name-plate data as actual data [5], [8]. The equivalent circuit parameters were then estimated using evolutionary techniques such as Particle Swarm Optimization (PSO) Algorithm, Jaya Optimization Algorithm (JOA) and Genetic Algorithm (GA). Eventually,

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the by minimizing the error between the measured power and voltage at different loading conditions and the estimated values are minimized to obtain the optimal estimated parameters [2], [19]–[22].

Chaotic Optimization Algorithm was used the name-plate and the load test data to estimate the parameters of single phase transformer in [23]. In [24], Bacterial Foraging Algorithm (BFA) is used to estimate the single- phase and three-phase transformer parameters by applying open and short-circuit experimental tests. Imperialist competitive and gravitational search algorithms (GSA) have been proposed to estimate the single-phase transformer parameters from name-plate data [25], In addition, Artificial Bee Colony Algorithm was used in [26] to estimate the transformer parameters. All of these algorithms can be applied using name-plate or load data during the operation of transformer without having to disconnect the transformer for testing purposes. Moreover, these algorithms can estimate three-phase transformer parameters as well as those of single-phase transformer [27], [28] and for optimal design of a three-phase high-speed flux reversal machine in [29].

Coyote optimization algorithm (COA) is a new meta-heuristic optimization algorithm designed in [30]. The coyote's social organization and exchanging experiences is the base of adaptation (optimization) to the environmental conditions. COA has been classified as both swarm intelligence and evolutionary heuristic. Several applications of COA are reported in the literature as for optimizing the estimated parameters of fuel cell [31] and for parameter estimation of solar cells [32].

In the current study, the COA is developed to estimate the optimal parameters of single and three phase transformers. This work has the following main features:

- This study proposed COA for parameters estimation of transformers;
- This work is applied to both single- phase and three-phase transformers;
- Parameter estimation of three and single-phase transformers using the proposed COA is assessed with those obtained by JOA and PSO competitive algorithms;
- The estimation process aims to realize the best voltage regulation and efficiency by accurate modeling of transformer equivalent circuit parameters;
- Experimental tests (open and short circuit tests) are done on single and three-phase transformer to verify the estimated parameters.

## II. STEADY STATE CHARACTERISTICS OF TRANSFORMER

The steady-state single phase equivalent circuit of the transformer is shown in Figure 1 [14].

Appling Kirchhoff voltage and current laws to the per-phase transformer equivalent circuit (Figure 1), the following relations can be obtained:

$$\underline{V}_1 = \underline{E}_1 + \underline{I}_1 \underline{Z}_1 \tag{1}$$

$$\underline{E}_1 = \underline{V}'_2 + \underline{I}'_2 \underline{Z}'_2 \tag{2}$$

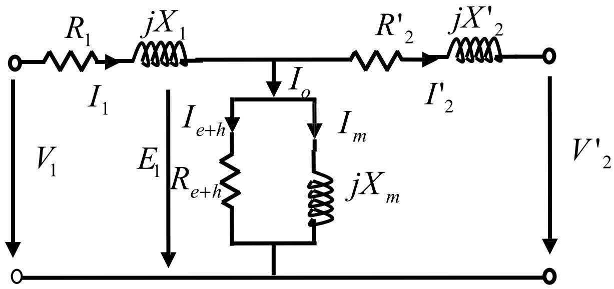


**FIGURE 1.** Per phase equivalent circuit of transformer.

$$\underline{E}_1 = \underline{I}_o \underline{Z}_{m_a} \tag{3}$$

$$\underline{I}_1 = \underline{I}_o + \underline{I}'_2 \tag{4}$$

From the four equations, the primary current $I_1$ and the primary induced voltage $E_1$ can be obtained as follows:

$$\underline{I}_1 = \frac{\underline{V}_1 + \underline{I}'_2 \underline{Z}'_2}{\underline{Z}_1 + \underline{Z}_m} \tag{5}$$

$$\underline{E}_1 = \underline{V}_1 - \underline{I}_1 \underline{Z}_1 \tag{6}$$

The referred secondary voltage will be:

$$\underline{V}'_2 = \underline{E}_1 - \underline{I}'_2 \underline{Z}'_2 \tag{7}$$

The core current $I_o$ can be obtained as an equivalent value to the core magnetizing current component $I_m$ and the core loss current component $I_{e+h}$ as follows:

$$\underline{I}_o = \frac{\underline{E}_1}{\underline{Z}_m} = \frac{\underline{E}_1}{R_{e+h}} - j\frac{\underline{E}_1}{X_m} = I_{e+h} - jI_m \tag{8}$$

The transformer voltage regulation is given as:

$$VR = \frac{V_1 - V'_2}{V_1} \tag{9}$$

The primary power factor $pf_1$, input power $P_{in}$, and the output power $P_o$ can be obtained as follows:

$$pf_1 = \cos(angle(\underline{I}_1)) \tag{10}$$

$$P_{in} = real(V_1 \times I_1^*) \tag{11}$$

$$P_o = real(V'_2 \times I_2'^*) \tag{12}$$

Efficiency of the transformer can be calculated from:

$$\eta_r = \frac{P_o}{P_{in}} \tag{13}$$

It is required to identify the equivalent circuit parameters $R_1, X_1, R_2, X_2, R_{e+h}, X_m$ accurately as possible. This goal can be achieved through an optimization algorithm.

## III. PROPOSED COYOTE OPTIMIZATION ALGORITHM

Coyote optimization algorithm (COA) is a new nature-inspired metaheuristic algorithm [30]. It is a population-based algorithm, which depends on the social organization and conditions of coyotes. COA has been classified as both swarm intelligence and evolutionary heuristic. The objective function is optimized based on the social organization and exchanging experiences among the coyotes. The population of coyotes consists of number of packs, *NP*; each pack contains $NC$ coyote. The total number of coyotes in all packs represents the population of the optimization problem. The solution of the optimization problem means the optimal adaptation to all social conditions. These social conditions of coyotes depict the d- space decision variables of the optimization problem.

The social condition *'soc'*, of the coyote in the $p^{th}$ pack at $t^{th}$ instant of time, is $soc_c^{p,t}$. These conditions of the coyote represent the decision variables $\overline{X}$ of a specified global optimization problem [24]. It is given as:

$$soc_c^{p,t} = \overline{X} = (x_1, x_2, \ldots\ldots, x_d) \tag{14}$$

The initial social conditions are started randomly for each coyote $c^{th}$ of $p^{th}$ at instant $t^{th}$ and $j^{th}$ dimension in the range of the lower and upper bounds, $LBj$ and $UBj$ of the decision variable as follows:

$$soc_{c,j}^{p,t} = LB_j + r_j \times (UB_j - LB_j) \tag{15}$$

where, $r_j$ is a real random number lies in the [0-1] range which generated using a uniform probability.

The objective function is obtained by evaluating the coyote's conditions corresponding to the current decision variables, as follows:

$$fit_c^{p,t} = f(soc_c^{p,t}) \tag{16}$$

The social organization of coyotes enables it to leave its pack or join to another one according to the current coyote in the pack, $NC$ (limited to 14 coyote inside the pack). The best solution to the optimization problem at $t^{th}$ instant of time of $P^{th}$ pack is 'alpha' for the global population. It is determined as follows:

$$alpha^{p,t} = \left\{ soc_c^{p,t} \middle| \arg_{c=(1,2,\ldots,N_c)} \min f(soc_c^{p,t}) \right\} \tag{17}$$

The COA enables the sharing of social conditions and links all information from the global population. COA, then, computes the cultural tendency of the pack, which is the median social condition of all coyote from that defined pack.

$$cult_j^{p,t} = \left\{ \begin{array}{ll} O^{p,t}_{\frac{(N_c+1)}{2},j}, & N_c \text{ is odd} \\ \dfrac{O^{p,t}_{\frac{N_c}{2},j} + O^{p,t}_{\frac{(N_c+1)}{2},j}}{2} & \text{otherwise} \end{array} \right\} \tag{18}$$

where $O^{p,t}$ is the ranked decision variables (i.e. social conditions) of all coyote inside the $p^{th}$ pack at $t^{th}$ instant for every $j$ in the space of decision variables, $d$.

The updating of coyote's new social conditions, $new\_soc_c^{p,t}$ depends on two factors; the first is the alpha influence, $\delta_1$, and the second is the cultural tendency influence $\delta_2$, as follows.

The influence $\delta_1$ is taken as the difference from a random coyote ($Cr_1$) inside the pack to the alpha coyote. On the other hand, the pack influence ($\delta_2$) is considered as the difference from a random coyote ($C_{r2}$) of a pack to the cultural tendency of that pack.

$$\delta_1 = alpha^{p,t} - soc_{cr1}^{p,t} \tag{19}$$

**TABLE 1.** Experimental tests of three and single phase transformers (cases 1 and 2).

| Variables | No load test | | SC test | | DC test | |
|---|---|---|---|---|---|---|
| | Case 1 | Case 2 | Case 1 | Case 2 | Case 1 | Case 2 |
| **Voltage (V)** | 222.2 | 228 | 23.72 | 20.8 | - | - |
| **Current (A)** | 0.11 | 0.05 | 1.08 | 0.18 | - | - |
| **P (W)** | 0.834 | 3.28 | 3.97 | 2.58 | - | - |
| **$R_1(\Omega)$** | - | - | - | - | 1.7 | 52.5 |
| **$R_2(\Omega)$** | - | - | - | - | 1.7 | 27.12 |

$$\delta_2 = cult^{p,t} - soc_{cr2}^{p,t} \tag{20}$$

$$new\_soc_c^{p,t} = soc_c^{p,t} + r_1\delta_1 + r_2\delta_2 \tag{21}$$

where, $r_1$ and $r_2$ are uniformly random numbers within the range [0-1].

The new value of the objective function is determined by evaluation of the new social conditions, as follows:

$$new\_fit_c^{p,t} = f(new\_soc_c^{p,t}) \tag{22}$$

At the next $(t+1)^{th}$ time instant, the decision is taken about the new social conditions according to the value of the objective function, as follows:

$$soc_c^{p,t+1} = \left\{ \begin{array}{ll} new\_soc_c^{p,t}, & new\_fit_c^{p,t} \le fit_c^{p,t} \\ soc_c^{p,t} & \text{otherwise} \end{array} \right\} \tag{23}$$

The global solution of the problem is that the social conditions of a coyote that best adapted itself to the environment. In order to keep the pack size static, COA computes the ages of all coyote inside a pack (in years) as $age_c^{p,t} \in N$. The birth of a new coyote is represented by a combination of the social conditions of two parents inside a pack, which are chosen randomly, as follows:

$$pup_j^{p,t} = \left\{ \begin{array}{ll} soc_{r_1,j}^{p,t}, & r \text{ and } j \le P_s \text{ or } j = j_1 \\ soc_{r_1,j}^{p,t}, & r \text{ and } j \ge (P_s + P_a) \text{ or } j = j_2 \\ R_j & \text{otherwise} \end{array} \right\} \tag{24}$$

where, $r_1$ and $r_2$ are random coyote inside $P^{th}$ pack. $j_1$ and $j_2$ represent two randomly dimensions of the optimization problem. $P_s$ and $P_a$ are the scatter and association probabilities, given by Eqs. (22)-(24). $R_j$ is a random number lies inside the decision variable bound of the $j^{th}$ dimension. The value of the real random number ran $d_j$ lies in the range [0-1], and generated using uniform probability.

$$P_s = 1/d \tag{25}$$

$$P_a = (1 - P_s)/2 \tag{26}$$

The birth and the death of coyotes are syncs as the following steps (Algorithm #1):

Step 1: Compute the group worse adapted to the environment than the pups, 'w' and the number of coyotes in this group, $'\varphi'$.

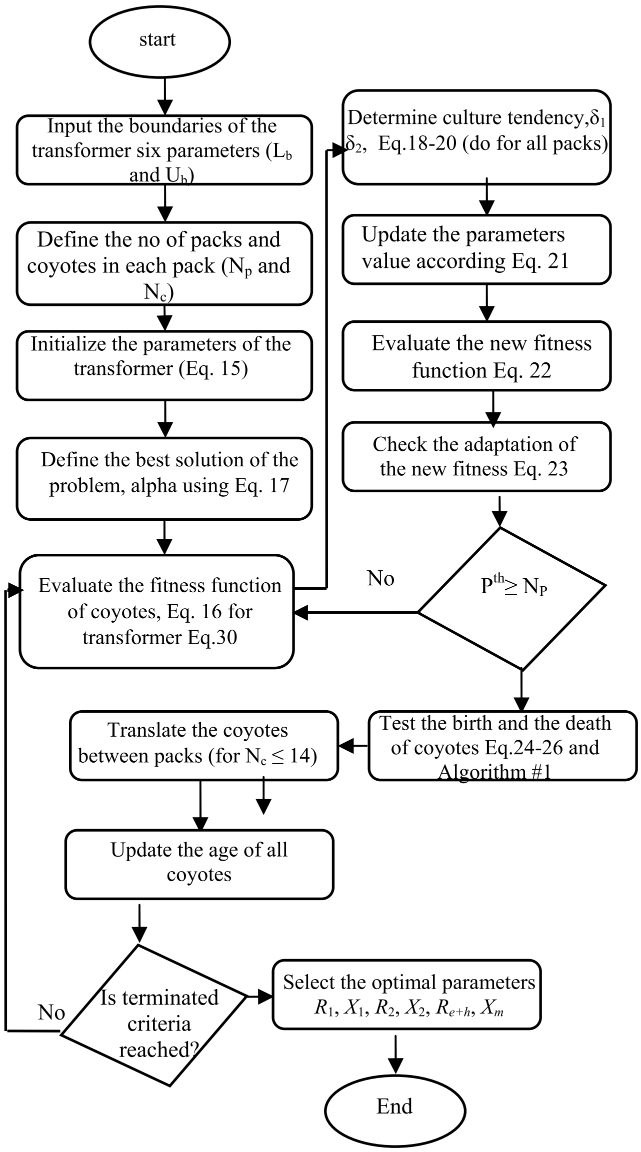


**FIGURE 2.** Proposed COA flowchart for transformer.

**TABLE 2.** Optimal parameters of three phase transformer Case 1 (4 kVA, 380/380 V).

| Algorithm | Name-plate | PSO | Jaya | Coyote |
|---|---|---|---|---|
| $R_1(\Omega)$ | 1.7 | 1.6889 | 1.731 | 1.7099 |
| $X_1(\Omega)$ | 10.84 | 10.7813 | 10.7237 | 10.7782 |
| $R_2(\Omega)$ | 1.7 | 1.7113 | 1.6685 | 1.69 |
| $X_2(\Omega)$ | 10.84 | 10.7889 | 10.8482 | 10.85 |
| $R_{r+h}(\Omega)$ | 59252 | 59254 | 59289 | 59200 |
| $X_m(\Omega)$ | 2021 | 2011.4 | 2023 | 2022 |
| Average error (%) | base | 0.0033 | 0.0083 | 0.0032 |

Step 2: Check if $\varphi$ equals 1then go to step3 else if $\varphi$ is greater than 1 go to step4 else the pub dies.

Step 3: The pub survives and the only coyote representing w dies.

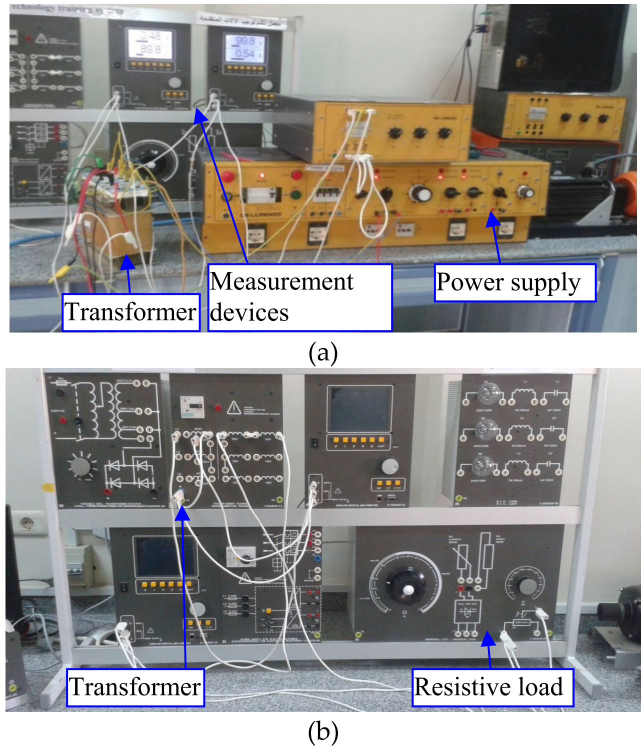


**FIGURE 3.** Photograph of the experimental setup: (a) three (Case 1) and (b) single (Case 2)phase transformers.

**TABLE 3.** Optimal parameters single phase transformer Case 2 ( 1 kVA, 230/230 V).

| Algorithm | Name-plate | PSO | Jaya | Coyote |
|---|---|---|---|---|
| $R_1(\Omega)$ | 52.5 | 50.087 | 50.112 | 51.75 |
| $X_1(\Omega)$ | 41.85 | 42.844 | 43.735 | 39.301 |
| $R_2(\Omega)$ | 27.12 | 30.211 | 30.186 | 28.154 |
| $X_2(\Omega)$ | 41.85 | 48.009 | 47.226 | 38.054 |
| $R_{e+h}$ $(\Omega)$ | 15849 | 15935 | 15932 | 15862 |
| $X_m(\Omega)$ | 47589 | 46757 | 46810 | 47812 |
| Average error (%) | base | 5.896 | 5.450 | 3.224 |

**TABLE 4.** Statistical indices of PSO, JOA and COA.

| Case | Algorithm | Best OF | mean OF | Median | Standard deviation | Variance |
|---|---|---|---|---|---|---|
| | COA | 8.8e-10 | 8.8e-10 | 8.8e-10 | 3.76e-23 | 1.41e-45 |
| #1 | JOA | 8.7e-10 | 9.7e-9 | 1.7e-9 | 3.1e-8 | 9.4e-16 |
| | PSO | 8.4e-10 | 9.9e-10 | 9.9e-10 | 6.9e-11 | 4.8e-21 |
| | COA | 4.2e-30 | 4.5e-14 | 3.2e-14 | 4.8e-14 | 2.3e-27 |
| #2 | JOA | 2.2e-12 | 9.9e-9 | 8.0e-9 | 8.8e-9 | 7.8e-17 |
| | PSO | 2.0e-15 | 6.1e-9 | 5.4e-9 | 1.2e-8 | 1.5e-16 |

Step 4: The pub survives and the oldest coyote in w dies. If two or more coyotes have the same age, the one which has less adaptive dies.

**TABLE 5. Simulation full load data of Case 2 (1 kVA, 230/230 V).**

| Algorithm | Tested | Calculated | PSO | Jaya | Coyote |
|---|---|---|---|---|---|
| $I_1$ (A) | 0.16 | 0.159 | 0.1589 | 0.1589 | 0.1589 |
| $\eta_{FL}$ | 0.863 | 0.859 | 0.859 | 0.859 | 0.859 |
| Pf | 0.99 | 0.988 | 0.9877 | 0.9877 | 0.9877 |
| SSAP | base | 4.323e-3 | 2.87e-11 | 1.017e-12 | 9.55e-14 |

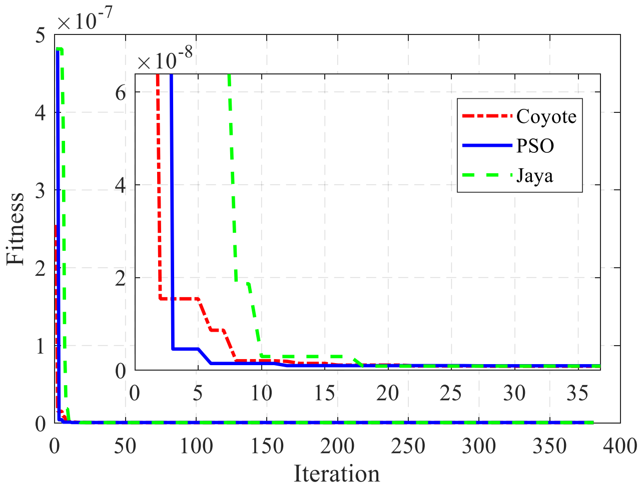


**FIGURE 4. Convergence curves of the objective function for transformer; Case 1(4 kVA, 380/380 V).**

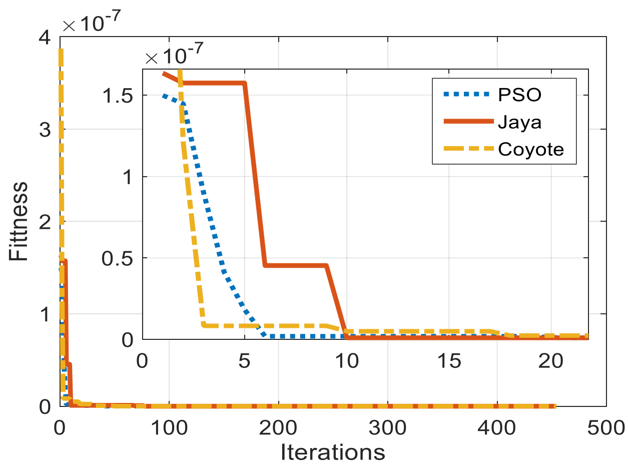


**FIGURE 5. Convergence curves of the objective function for transformer; Case 2 (1 kVA, 230/230 V).**

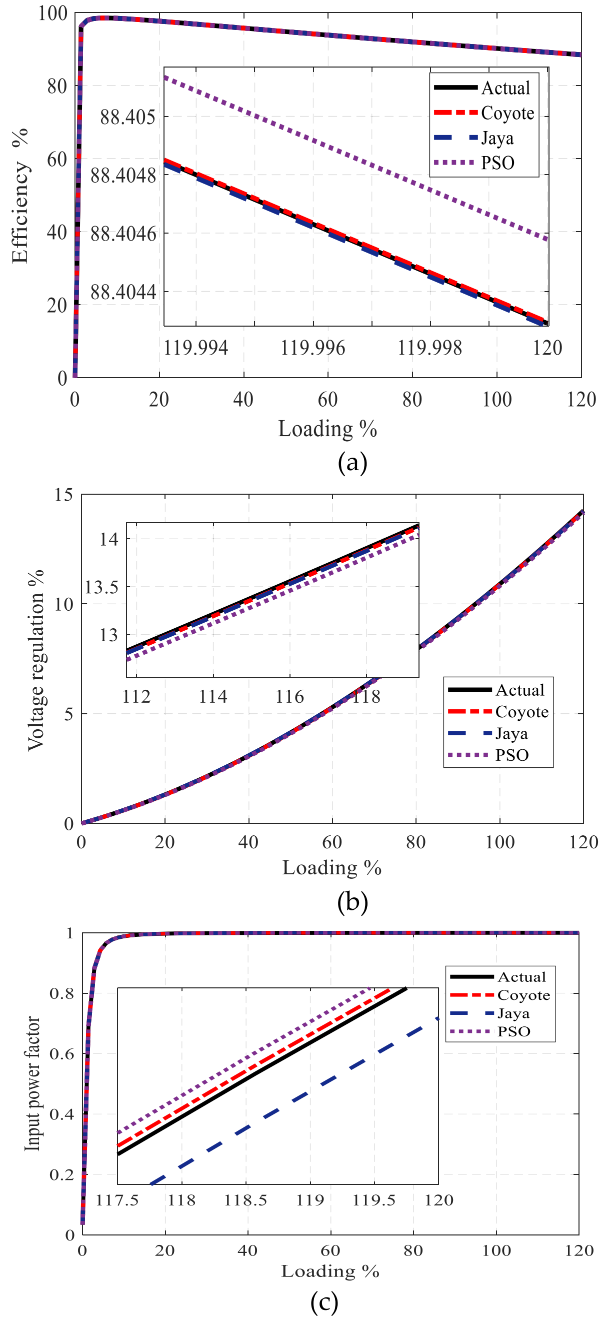


**FIGURE 6. Performance of 4 kVA, 380/380 V, 50Hz 3$\varphi$ transformer; (a): Efficiency%, (b) Voltage regulation% and (c) Power factor.**

Finally, the optimal values of transformer parameters ($R_1$, $X_1$, $R_2$, $X_2$, $R_{e+h}$, $X_m$ ) are reached by evaluating the objective function and checking the maximum number of iterations.

## IV. PARAMETER ESTIMATION OF SINGLE- PHASE AND THREE-PHASE TRANSFORMERS

The objective function of the transformer parameter estimation problem aims to minimize the deviation between the estimated and the manufacturer's data. The optimized parameters, $R_1$, $X_1$, $R_2$, $X_2$, $R_{e+h}$, $X_m$ are affecting Eqs.(8)-(13) that, in turn, affect the primary current, efficiency, and the power factor of the load.

The calculated values are required to be assessed with the manufacturer's data. To realize the convergence, the sum of square absolute percentage error (*SSAPE*) between manufacturer's data and the estimated values must be minimized. COA and JOA as a meta-heuristic optimization algorithm are

**TABLE 6. Simulation full load data of Case 1 (4kVA, 380/380 V).**

| Algorithm | Calculated | PSO | Jaya | Coyote |
|---|---|---|---|---|
| $I_1$ (A) | 7.0424 | 7.0424 | 7.0424 | 7.0424 |
| $\eta_{FL}$ | 0.9013 | 0.9013 | 0.9013 | 0.9013 |
| Pf | 0.9999 | 0.9999 | 0.9999 | 0.9999 |
| SSAP | base | 9.753e-10 | 9.168e-10 | .8774e-10 |

applied to minimize the objective function of the problem.

$$f_1 = \frac{e\eta_r - m\eta_r}{m\eta_r} \tag{27}$$

$$f_2 = \frac{eI_1 - mI_1}{mI_1} \tag{28}$$

$$f_3 = \frac{epf - mpf}{mpf} \tag{29}$$

$$SSAPE = f_1^2 + f_2^2 + f_3^2 \tag{30}$$

The problem objective function is expressed as:

$$OF = \min(SSAPE) \tag{31}$$

Eq. (31) is subjected to the boundary constraints of the problem control variables as:

$$\begin{aligned} &R_1^{\min} \leq R_1 \leq R_1^{\max}, R_2^{\min} \leq R_2 \leq R_2^{\max} \\ &X_1^{\min} \leq X_1 \leq X_1^{\max}, X_2^{\min} \leq X_2 \leq X_2^{\max} \\ &R_{e+h}^{\min} \leq R_{e+h} \leq R_{e+h}^{\max}, X_m^{\min} \leq X_m \leq X_m^{\max} \end{aligned} \tag{32}$$

Figure 2 shows the flowchart of the proposed COA for estimating the parameters of single and three -phase transformers. In this study, COA has 10 packs, each of them contains 10 coyotes. Thus, the population number is 100 coyotes. The maximum number of iterations is set to 350 and it is considered as the stopping criterion of the optimization process. JOA and PSO parameters are customized from [33]–[37].

## V. CASE STUDIES

The effectiveness of the proposed COA is verified through the estimation of the parameters of single and three-phase transformers. Theses transformers are described as:

*Case 1:* 4 kVA, 380/380 V, 50 Hz, three-phase transformer: Open circuit, short circuit and DC tests are carried out to obtain the actual parameters of the equivalent circuit. Photograph of the experimental implementation is provided in Figure 3.

*Case 2:* 1 kVA, 230/230 V, 50 Hz, single-phase transformer, Open circuit, short circuit, DC and load tests are carried out to obtain the actual parameters of the equivalent circuit.

Table 1 lists the recorded measurements at no load and short circuit tests for single and three-phase transformers. In these cases, the actual data of the transformers have been obtained using the open and short-circuited experimental tests. The open circuit test is performed at the nominal voltage and the measured current and power are used to determine

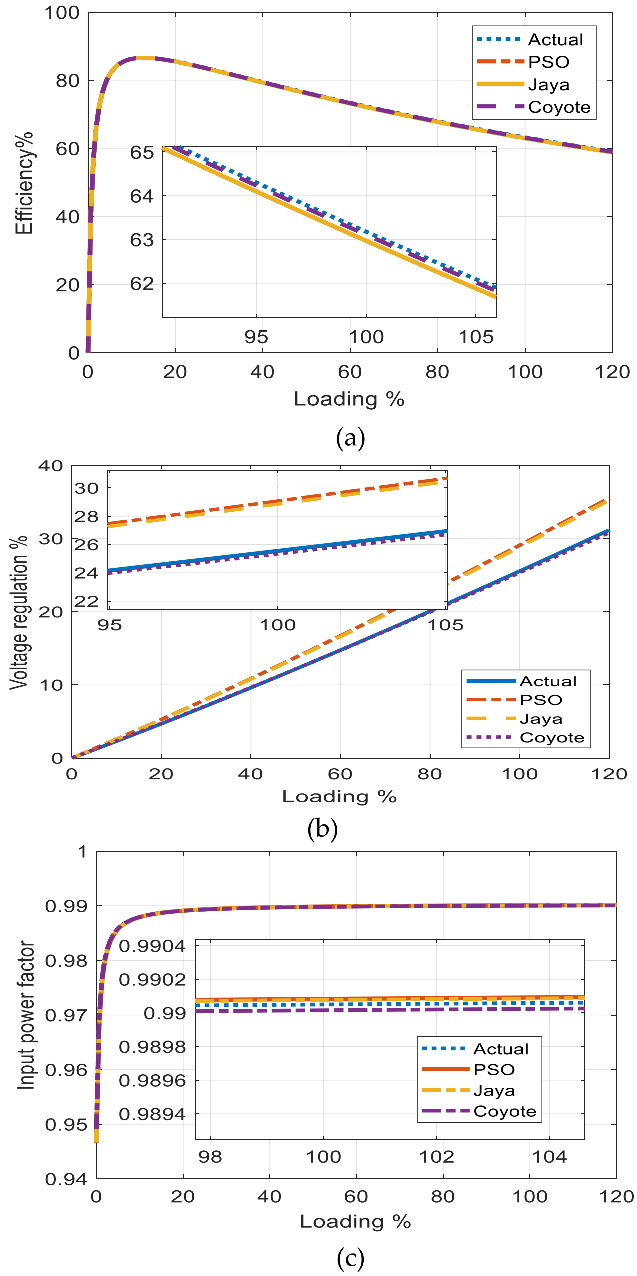


**FIGURE 7. Performance of Case 2, 1 kVA, 230/230 V, 50 Hz single phase transformer; (a) Efficiency%, (b) Voltage regulation% and (c) Power factor.**

the core resistance and magnetizing reactance i.e. $R_{e+h}$, and $X_m$ respectively. In addition, short-circuit test measurements (voltage, current and power) are used to determine the primary and secondary resistances and leakage reactances i.e. $R_1, X_1, R_2, X_2$ respectively.

The parameters of both cases are estimated optimally using the COA compared with PSO, Jaya and with those customized from the name-plate and loading data. The obtained results using the competitive algorithms are compared with the actual values, as explained in Tables 2 and 3. The estimated parameters are used to calculate the transformer

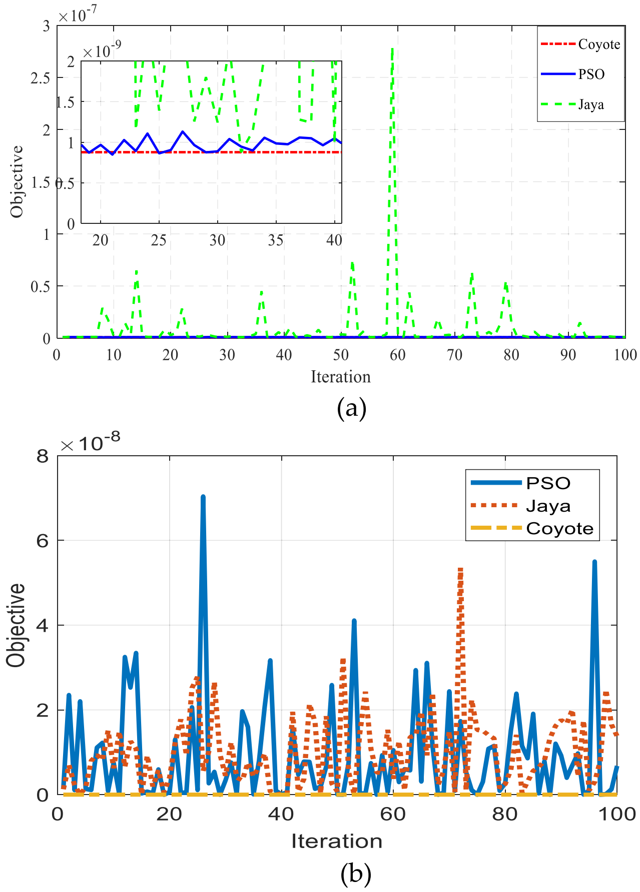


**FIGURE 8. Robustness of the competitive algorithms (PSO, JOA and COA); (a) Case 1 and (b) Case 2.**

current, power factor, voltage regulation, and efficiency at full-load conditions.

Tables 4 and 5 compare the estimated and actual performance (current, power factor, and efficiency) at full load besides the voltage regulation at different load conditions. The results prove that the proposed COA gives the most accurate operating performance. In Case 1, the errors obtained are 9.753e-10 with PSO, 9.168e-10 with Jaya, and 9.168e-10 with COA. In Case 2, it is cleared that COA has the lowest error for estimating the transformer performance. Good convergences of the three competitive algorithms are illustrated in Figs. 4 and 5 for Cases 1 and 2, respectively. It was noticed that PSO converges faster than the others; however, COA has reached the lowest objective function than JOA and PSO. Figure 6 shows the performance using the estimated parameters of Case 1 compared with those of the actual data. High closeness between estimated efficiency and input power factor are noticed at different loading percentage to the actual characteristic using COA, then JOA and later PSO. However, voltage regulation optimized by JOA is the nearest to the actual curve. Figure 7 shows the performance data of Case 2 compared with the reported name-plate data. Estimated efficiency and voltage regulation using the proposed COA are very close to the actual values. JOA and COA outperform in estimating the input Power factor.

As the objective function compromise efficiency, voltage regulation, and input power factor, it can be concluded that best estimation of transformer parameters is obtained. All results show the effectiveness of the proposed competitive algorithms to identify the transformer parameters compared with the actual nameplate data. The proposed COA outperforms the other in performance verification.

To verify the robustness of the proposed algorithms, 100 separate runs are applied to COA, JOA and PSO for Cases 1 and 2. Figure 8 illustrates the robustness of the three algorithms. It is clear that, the proposed COA has the highest robustness, then JOA and later PSO. Table 4 presents the statistical indices of the proposed method at the defined cases.

## VI. CONCLUSION

In this paper, the COA optimization algorithm has been proposed for estimating accurate model parameters of the single and three-phase transformers. The estimated parameters of three competitive algorithms i.e. PSO, JOA and COA are used to calculate the operating performance of the transformer at different loading conditions. The results obtained have been compared with the recorded experimental results. The results signify the effectiveness and reliability of the proposed (COA) in estimating accurate model of the transformers. The COA realizes rapid, smooth, and steady convergence than PSO and Jaya. According to the results obtained, the COA has the ability and stability to identify optimal parameters and accurate performance of both single and three phase transformers. It can be concluded from all results obtained that COA is more simple, stable, global outperformance optimization algorithm in estimating the power transformer parameters compared to PSO and JOA.

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